



Toward a Real-Time Measurement-Based System for Estimation of Helicopter Engine Degradation Due to Compressor Erosion

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Prepared for the
Forum 63
sponsored by the American Helicopter Society International (AHS)
Virginia Beach, Virginia, May 1–3, 2007

National Aeronautics and
Space Administration

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Acknowledgments

The authors gratefully acknowledge the financial support of the Army Research Laboratory Director's Research Initiative grant FY06-VTD-02. The authors wish to thank Nick Hein and Chris Rowe of the U.S. Navy NAVAIR, Patuxent River, Maryland, for providing and discussing the sand ingestion data, as well as Tim Large and Mark Beeman of the U.S. Army AMRDEC—AED, Huntsville, Alabama, for providing and discussing the Health Usage and Monitoring System (HUMS) data.

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Abstract

This paper presents a preliminary demonstration of an automated health assessment tool, capable of real-time on-board operation using existing engine control hardware. The tool allows operators to discern how rapidly individual turboshaft engines are degrading. As the compressor erodes, performance is lost, and with it the ability to generate power. Thus, such a tool would provide an instant assessment of the engine's fitness to perform a mission, and would help to pinpoint any abnormal wear or performance anomalies before they became serious, thereby decreasing uncertainty and enabling improved maintenance scheduling. The research described in the paper utilized test stand data from a T700-GE-401 turboshaft engine that underwent sand-ingestion testing to scale a model-based compressor efficiency degradation estimation algorithm. This algorithm was then applied to real-time Health Usage and Monitoring System (HUMS) data from a T700-GE-701C to track compressor efficiency on-line. The approach uses an optimal estimator called a Kalman filter. The filter is designed to estimate the compressor efficiency using only data from the engine's sensors as input.

Notation

FADEC	Full Authority Digital Engine Control
Ng	gas generator speed
Np	power turbine speed
PS_3	compressor exit static pressure
Q	torque
SHP	Shaft Horsepower
$T_{4.5}$	Turbine Gas Temperature
W_f	fuel flow
Δx	change in a variable x
η	efficiency
η_{Comp}	compressor efficiency
η_{GG}	gas generator turbine efficiency
η_{PT}	power turbine efficiency
σ_x	standard deviation of a variable x
c	corrected (subscript)

Introduction

Sand ingestion is a significant problem for helicopters operating in desert terrain. In Afghanistan and Iraq, operators have found that the sand erodes the compressor to the point where the ensuing power loss makes the helicopter unfit to operate after relatively few missions. This results in engines being pulled from service for overhaul at a much higher frequency than those operated under less harsh conditions. The increased maintenance requirement severely hampers the warfighters' ability to perform because the availability of assets is much less certain—mission readiness suffers and maintenance costs skyrocket.

All engines wear naturally with use. In general, as turboshaft engines degrade, their performance shifts away from that of a new engine. Over time they tend to run hotter than a new engine to produce the same power. The deterioration takes the form of reduced efficiency and altered flow capacity of the engine components, increased seal leakage, etc.; these variables collectively describe the engine's "health" and are called the engine *health parameters*. Because degradation negatively impacts engine power and it is important to recognize when power is compromised, complex nonlinear models have been developed to predict a turboshaft engine's available power, provide virtual sensors, and perform fault detection (refs. 1 to 3). These models attempt to match the engine outputs by adjusting their health parameters or similar-type variables to minimize the residuals, in the process generating health parameter estimates that provide the best fit to the engine data.

The degradation process is exacerbated by operation in a harsh environment. In particular, turboshaft engines operating in the sandy deserts of Iraq and Afghanistan have had to be overhauled after as little as 50 to 100 hr of operation, while engines operating under less extreme conditions can remain on wing at least 10 times that long (refs. 4 and 5). The desert operation of a turboshaft engine results in a special case of deterioration because it is directly attributable to erosion caused by sand particles, and although some of the literature acknowledges that there may be shifts

in a variety of health parameters, in general the performance loss is attributed substantially if not exclusively to compressor efficiency reduction (refs. 4, 6 to 8).

The current practice for determining the fitness for service of a T700 turboshaft engine, for instance, is through a procedure called a Health Indicator Test (HIT) check, which is performed daily on the ground. It involves checking that the available Turbine Gas Temperature ($T4.5$) margin at a specified steady state rotor speed and torque are adequate for each engine individually; failing the test means that the vehicle is grounded (ref. 9). This test requires pilot involvement, and is affected by ambient conditions. It provides simply a pass/fail grade, requiring the pilot only to make a notation if the margin is acceptable but below a threshold.

It would be beneficial to actually be able to track engine performance deterioration rather than just receive a passing grade. The ability to track the engine degradation would provide an instant evaluation of the engine's health, and would help to detect any abnormal wear or performance anomalies early, thus decreasing uncertainty and enabling improved maintenance scheduling.

The objective of this study is to demonstrate an algorithm that can estimate engine performance deterioration due to sand ingestion from real-time data. The algorithm is based on a linear approach, and its simple structure lends itself well to real-time operation. The following sections will introduce the linear estimation technique, set up and validate the estimator using a T700 engine, and finally run the algorithm with actual flight data to show how it might work in a real application. All data have been sanitized for publication.

Model-Based Approach

An open-loop turboshaft engine can be modeled well by a linear discrete time system of the form

$$\begin{aligned} x(k+1) &= Ax(k) + Bu(k) + Lp + w(k) \\ y(k) &= Cx(k) + Du(k) + Mp + v(k) \end{aligned} \quad (1)$$

where k is the time index, $x(k)$ is the state vector at time k , $u(k)$ is the input vector, $y(k)$ is the output vector, p is the health parameter vector, $w(k)$ and $v(k)$ represent process noise and measurement noise respectively, and A , B , C , D , L , and M are matrices of appropriate dimension. It is clear from equation (1) that the health degradation, represented by p , is a set of input biases which manifest themselves as shifts in the state and output variable values. This concept agrees with the previous discussion of $T4.5$, the measured temperature

used in the HIT check, increasing as the engine deteriorates. As long as the linear model represents the true engine behavior fairly accurately, a vast array of linear tools can be brought to bear on the problem of estimating the engine health on-line.

In this work a recursive algorithm called a Kalman filter is used to directly estimate the engine's health condition based on measured data. This is a well-established linear technique that uses a dynamical model of the system to estimate unmeasured state variables optimally in a least squares sense as

$$\begin{aligned} \hat{x}(k|k) &= \hat{x}(k|k-1) \\ &+ K(y(k) - C\hat{x}(k|k-1) - Du(k)) \quad (2) \\ \hat{x}(k+1|k) &= A\hat{x}(k|k) + Bu(k) \end{aligned}$$

where $\hat{x}(k+1|k)$ is the estimate of $x(k+1)$ given measurements up through time k , and K is the optimal Kalman gain matrix. The Kalman gain matrix is computed as a function of the linear model whose state is to be observed (ref. 10). Part of the Kalman filter design process includes the determination of weighting matrices which are related to sensor noise and model accuracy, and affect tracking speed. Kalman filters have been used successfully in the past to estimate engine health information from turbofan engine test data (ref. 11). An engine that has a Full Authority Digital Engine Control (FADEC) (such as many modern turbofan engines and a planned upgrade to the T700-GE-701D) is capable of running a diagnostic scheme such as a Kalman filter during the control update time (ref. 12).

Notice that p in equation (1) is not a function of k , that is, it is considered to be constant relative to the engine dynamics. Thus equation (1) can be rewritten in an algebraically equivalent form that incorporates p in an augmented state vector.

$$\begin{aligned} \begin{bmatrix} x(k+1) \\ p \end{bmatrix} &= \begin{bmatrix} A & L \\ 0 & I \end{bmatrix} \begin{bmatrix} x(k) \\ p \end{bmatrix} + \begin{bmatrix} B \\ 0 \end{bmatrix} u(k) + w(k) \\ &= A_{Aug} x_{Aug}(k) + B_{Aug} u(k) + w(k) \\ y(k) &= \begin{bmatrix} C & M \end{bmatrix} \begin{bmatrix} x(k) \\ p \end{bmatrix} + Du(k) + v(k) \quad (3) \\ &= C_{Aug} x_{Aug}(k) + Du(k) + v(k) \end{aligned}$$

This manipulation allows p to be estimated by a Kalman filter (eq. (2)). The caveat with this approach is that the number of health parameters that may be observed is limited to at most the number of sensed variables on the engine (ref. 13), and specifically in this case to the number of sensed variables affected by deterioration. This limitation is often a drawback in the

general model-based approach because the influence of unaccounted-for health parameters can be smeared across the estimated values (ref. 14). In the specific problem being addressed however, that of sand ingestion, it is assumed that this is not an issue because the vast majority of deterioration tends to be attributed to one health parameter: compressor efficiency.

This approach will be applied to data from a T700 engine, which will be described next.

The T700 Engine Model

The T700 turboshaft engine is 1600 horsepower-class, modular, two-spool engine (fig. 1) consisting of a gas generator section and a free power turbine (ref. 15). The gas generator section is made up of a five-stage axial and a single-stage centrifugal compressor, a low fuel pressure through-flow annular combustion chamber, and an air-cooled, two-stage, axial-flow, high-pressure turbine. The free power turbine is a two-stage, uncooled, axial-flow type. There exists a one-way coupling between the power turbine and the gas generator, i.e., the power turbine extracts work from the gas turbine cycle but does not otherwise affect it. The power turbine is controlled to a constant speed.

In this work, a linear T700 model (ref. 16) was used to represent the baseline (undegraded) engine. This model has the form

$$\begin{aligned} x(k+1) &= Ax(k) + Bu(k) \\ y(k) &= Cx(k) \end{aligned} \quad (4)$$

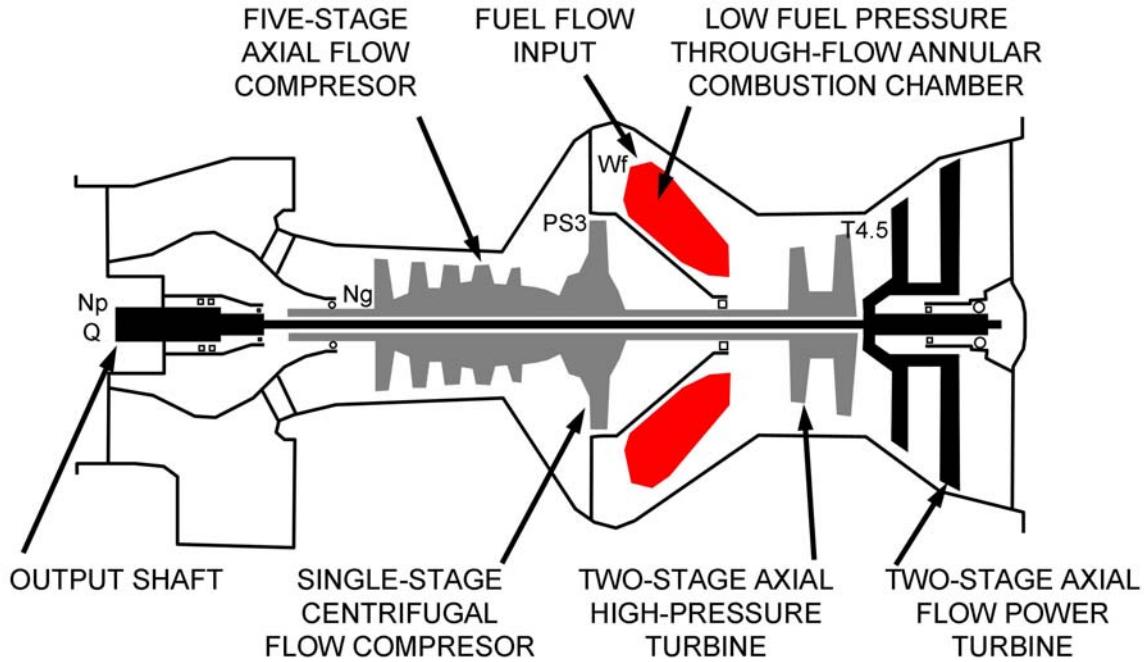


Figure 1.—Cross-section of a T700 turboshaft engine showing the rotating components and sensor locations.

This model was developed for use in a diagnostic application, and the state variables have no physical meaning, only the inputs and outputs represent actual engine variables. The input variables are W_f and N_p , and the output variables are N_g , Q , $T_{4.5}$, and PS_3 . The A matrix captures the dynamics of the engine (ref. 16).

Comparing to equation (1), the model in equation (4) has no D , L , or M matrices. The D matrix, which would appear as part of the baseline engine model, is zero. To incorporate the effects of component deterioration on the engine output variables, the influence coefficient matrices L and M need to be determined; these were not part of the original baseline model (ref. 16). Since the state variables in the baseline linear model have no physical meaning, L is set equal to zero. Therefore in this model the shifts in the output variables must be completely accounted for through the M matrix.

The sand ingestion data, which will be discussed next, were used to scale the steady state gain of the baseline model (fuel flow to each of the output variables) and also to construct the M matrix.

The Data Set

The data set consists of performance data from a sand ingestion test conducted at the Outdoor Engine Test Facility, Naval Air Warfare Center, Patuxent River, Maryland. Over a two-month period, 70 lbs of sand was ingested through a T700-GE-401 turboshaft

engine to evaluate the effects of sand erosion on engine performance. The sand eroded the engine components, thus altering their efficiency. Alternating with the sand ingestion runs were performance runs, carried out to determine how the engine was operating. Each performance run consisted of generating multiple steady state data points at various values of $T4.5$ by varying the load while maintaining power turbine speed. Altogether there were 115 steady state points generated in 25 performance runs. Data collected included the steady state values of Wf , Np , Q , Ng , $T4.5$, $PS3$, and ambient conditions. Before the sand ingestion testing was begun and again once it was complete, the engine components were evaluated to determine their overall efficiency and thus their change in efficiency due to erosion. Using these data, the linear model in equation (3) was scaled to enable the on-line estimation of the health degradation due to erosion.

Model Scaling

The first step in the scaling process was to put the data into a usable form. Engine operation is strongly influenced by the ambient conditions, among other things, and it is hard to compare raw data taken on different days under different conditions. A way around this is to *correct* the engine variables, that is, to adjust all of the data to a common point, in this case sea level standard day (ref. 17). This adjustment, which is shown in the appendix, significantly reduces the scatter in the data and makes it easier to analyze. It also makes it easier to design controllers and estimators because fewer operating points need to be accounted for. Correcting data might collapse it enough to enable the use of a single point design rather than a series of designs. The corrections based on ambient conditions handle the majority of the necessary data adjustment, but many other corrections may be applied to account for humidity, fuel temperature, and any other type of variation between the actual and “defined” conditions to potentially reduce the data spread even further.

In steady state, $x(k+1) = x(k)$, so the steady state outputs of the open-loop engine (eq. (4)) may be represented as

$$\begin{aligned} x &= Ax + Bu \\ y &= Cx \\ \Rightarrow x &= (I - A)^{-1}Bu \\ y &= C(I - A)^{-1}Bu \end{aligned} \quad (5)$$

This gives the steady state relationship between the input Wf and each of the outputs within the linear range. The steady state gain of the baseline engine, which is needed for scaling the linear model, can be

determined using the corrected data. Figures 2 to 5 show the highly linear relationship between Wf and each of the output variables. In these figures, the color bar on the right indicates when the data were collected; the earliest, at the beginning of the sand ingestion testing, is blue, the latest, at the end of the sand ingestion testing, is red. The line on each of the figures represents the steady state input-output relationship of the baseline engine, thus its slope represents the steady state gain. It is assumed that the steady state gain is not influenced by degradation, consistent with equation (1). Thus the lines were obtained through a least squares fit, using baseline data (earliest run) as well as degraded data (later runs). In both figures 2 and 3, the data seem to form a single line, so in each case all data points (except the two at the lower left, which are out of the linear range) were used to determine the slope and y-intercept of the line. In figures 4 and 5, the data sets from different performance runs form lines that are nearly parallel. Thus the average of these slopes was taken to represent the steady state gain for $T4.5$ and $PS3$. After determination of the slope, the y-intercept of each line was computed using only the data from the earliest run (the baseline condition). Thus the lines in figures 4 and 5 characterize the input-output relationship at the baseline condition, and as the engine degrades, these relationships shift up or down, which is expected (ref. 18).

It is not shown here, but obviously the output variables are uncorrelated with Np , since it is held constant while they vary. Thus the column of B corresponding to the Np input in equation (4) is multiplied by a small scale factor, maintaining the model form but rendering this input inconsequential. This essentially reduces the number of inputs to one: Wf . Now it is straightforward to match the steady state gains of the model to those determined from the data. The correct steady state gains (eq. (5)) were obtained by scaling the C matrix in the engine model (eq. (4)) to match the data. This was accomplished by multiplying the row of C corresponding to the specific output variable by an appropriate value so that equation (5) matched the slopes determined from the data.

It is counterintuitive that Ng (fig. 2) and Q (fig. 3) do not seem to shift as the engine degrades, but it should be noted that even if Q does not shift from the baseline condition, the degraded engine still cannot produce as much torque at high loads because the increased $T4.5$ will hit a controller temperature limit sooner than for a new engine, restricting fuel flow and thus limiting power.

Notice that for $T4.5$ (fig. 4), the line has a breakpoint at which the slope changes. Since the data are used with a linear model, the values must actually represent deviations from a trim value. Thus, once the data were

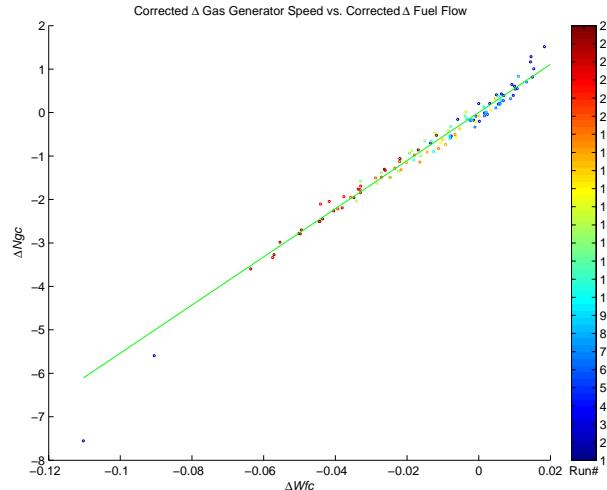


Figure 2.—Corrected ΔN_g vs. corrected ΔW_f , steady state sand ingestion data, units are arbitrary.

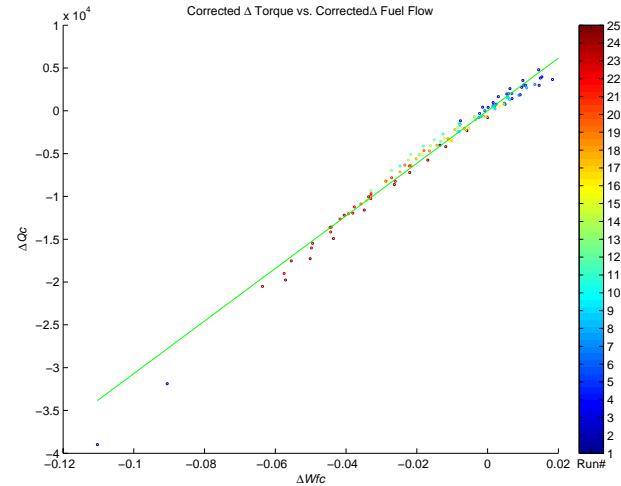


Figure 3.—Corrected ΔQ vs. corrected ΔW_f , steady state sand ingestion data, units are arbitrary.

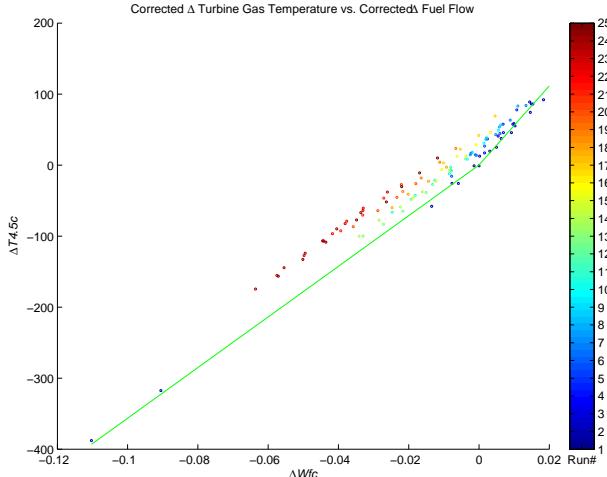


Figure 4.—Corrected $\Delta T_{4.5}$ vs. corrected ΔW_f , steady state sand ingestion data, units are arbitrary.

corrected, a trim point was selected and subtracted from each element of the data set; here the trim value corresponds to the point where the discontinuity in the slope of figure 4 occurs. Thus all results, starting with figure 2, are based on deviations from the corrected trim point.

The final step in the model development was the determination of the influence coefficient matrix M from equation (3), with L assumed to be zero. It is reasonable for L to equal zero because it affects the state variables, which have no physical meaning in this linear model, and the shifts in output variables ($T_{4.5}$ and $PS3$) can be completely captured through the M matrix. Table 1 shows the direction of influence of the efficiency shifts (losses) on the measured variables

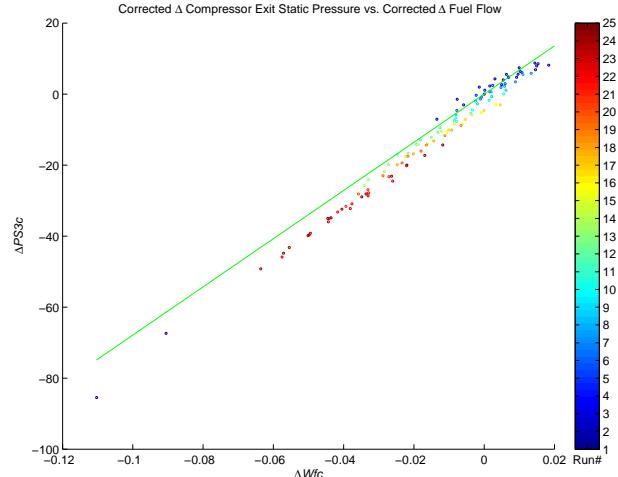


Figure 5.—Corrected $\Delta PS3$ vs. corrected ΔW_f , steady state sand ingestion data, units are arbitrary.

based on information in the literature (refs. 19 to 21), and the data.

Based on the sand ingestion results, the influence of degradation on Q and N_g was set to zero, the influence on $T_{4.5}$ was set to be negative (it increases as efficiency decreases) and the influence on $PS3$ was set to be positive (it decreases as efficiency decreases). Two points must be made here. First, the effect of the power turbine efficiency shift is apparently not observable in the measured parameters since Q is the only variable measured downstream of the power turbine and it shows no change with deterioration, implying that η_{PT} cannot be estimated. Second, since only two sensed variables are affected by the degradation, only two component efficiencies at most

can be estimated (or two combined effects, since $\Delta\eta_{\text{Comp}}$ actually represents the combined shift in the axial and centrifugal compressors). Thus potentially only η_{Comp} and η_{GG} can be individually estimated, and if $\Delta\eta_{\text{PT}}$ is truly not observable from the measured data, the fact that the entire shift is attributed to $\Delta\eta_{\text{Comp}}$ and $\Delta\eta_{\text{GG}}$ does not introduce error in the estimates. However, efficiency shifts will be individually observable only if their effects are linearly independent of each other, i.e., if the columns of M are linearly independent. Looking at table 1, it is clear that shifts in η_{Comp} and η_{GG} have similar effects on the output variables, making it hard to distinguish between them. Thus in this case, η_{Comp} and η_{GG} can be lumped into a single efficiency parameter, η . This implies that M is a single column, similar to the “Data” column in table 1.

The engine that underwent the sand ingestion testing was evaluated pre- and post-test to determine the total efficiency shift of the components due to erosion. The shift, $\Delta\eta$, was assumed to be the direct cause of the shift in $T4.5$ and $PS3$ and thereby used to scale the M matrix of the linear model of the T700 engine to account for degradation. Post-test analysis of the eroded engine components indicated a decrease in efficiency of the three components. For illustrative purposes, say $\Delta\eta_{\text{Comp}} = -1.8$ percent, $\Delta\eta_{\text{GG}} = -0.7$ percent, and $\Delta\eta_{\text{PT}} = -0.5$ percent. It was noted that this pattern of degradation is atypical and that in the field primarily η_{Comp} is affected. Although the sand ingestion data do not represent the results of true desert operation, the implementation used in this effort is still applicable for that situation. While shifts in three efficiencies occurred during the testing, η_{PT} is not observable, and $\Delta\eta_{\text{Comp}}$ and $\Delta\eta_{\text{GG}}$ have similar effects and thus are lumped together into one parameter, $\Delta\eta$, which is estimated and all deterioration attributed to it. The effect of this lumped parameter is similar to that of η_{Comp} alone had there been no change in η_{GG} , which is the case with desert operation. Here $\Delta\eta = \Delta\eta_{\text{Comp}} + \alpha\Delta\eta_{\text{GG}}$ where $\alpha\Delta\eta_{\text{GG}}$ corresponds to an equivalent value of $\Delta\eta_{\text{Comp}}$ that would produce a similar shift in the output variables; for the example, say $\alpha = 1$.

Since the actual degradation values are known, the elements of M must be selected as the ratio of the total shift in measured variables over the sand ingestion

testing to the efficiency shift, with signs that correspond to the data influences in table 1. Thus the elements of the M matrix are computed as $[0 \ 0 \ \Delta T4.5 \ \Delta PS3]^T = M\Delta\eta$. The Kalman filter was then generated based on equation (3) using the matrices from equation (4) (ref. 16) and M , with D and L zero. Because of the breakpoint in the $T4.5$ slope, two different Kalman gains were computed and the appropriate one used depending upon whether Wf was above or below the trim value. The piecewise linear approach could be extended to lower power levels, given enough data to generate the additional linear models.

Results

The objective of this effort was to demonstrate the feasibility of estimating engine deterioration on-line in real time. This required dynamic data and an estimator appropriate for the on-line application. The “dynamic” data set was created from the performance run data by first taking the 115 data points in order, each consisting of a set of steady state input/output values, and “holding” the values for 500 samples each (100 sec at five samples/second), thus generating a time series made up of steps for each variable. The time series data were then low pass filtered to round the steps in an effort to mimic dynamic performance—the intention was not to add artificial T700 engine dynamics, just to provide a smooth transition between steady state points. Finally, noise was added to each variable. The sequence of the model input variable Wf is shown in figure 6.

Running this data set through the Kalman filter simulated real-time, dynamic operation of the system, although the data sequence was generated with steady state data. The estimation performance of the Kalman filter is shown in figures 7 and 8. The sequences of residuals (differences between estimated and actual measurements) for the output variables Ng , Q , $T4.5$, and $PS3$ are shown in figure 7. The efficiency estimate, along with the average estimate from each performance run, is shown in figure 8. Clearly the result matches the known value (the difference of the lumped efficiency shift $\Delta\eta = \Delta\eta_{\text{Comp}} + \Delta\eta_{\text{GG}} = -2.5$ percent, between the end points) as seen from the estimation average.

TABLE 1.—DEVELOPMENT OF M (Wf , AND Np HELD CONSTANT) FROM THE DATA AND THE LITERATURE

Variable	Data	Literature		
		η_{Comp} (loss)	η_{GG} (loss)	η_{PT} (loss)
Ng	unchanged	decreased	decreased	unchanged
Q	unchanged	decreased	decreased	decreased
$T4.5$	increased	increased	increased	unchanged
$PS3$	decreased	decreased	decreased	unchanged

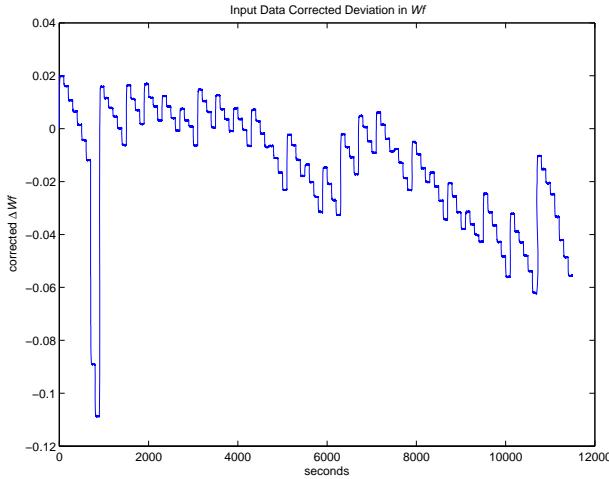


Figure 6.—Corrected input variable W_f , deviation from trim, arbitrary units.

Recall that each performance run consisted of several steady state points at different loads but the same

deterioration level, so the stair-stepping effect seen in figure 8 is a function of power level. The deterioration level at the in-between points (during the sand ingestion testing) is not known so these intermediate results cannot be validated, but show a general downward trend from the start point to the end point which is what one would expect. This helps to build confidence that the estimator is working as intended.

The development and validation of an on-line component efficiency estimation tool using the sand ingestion data is now complete. However, in order to make the estimator more practical, a significant implementation issue must still be considered, that of a reduced data set. This is discussed next.

Practical Considerations

Although Full Authority Digital Engine Controllers (FADECs) are planned for use on the T700-GE-701D, current T700s without a digital controller have few digital measurements available. In fact, there is no

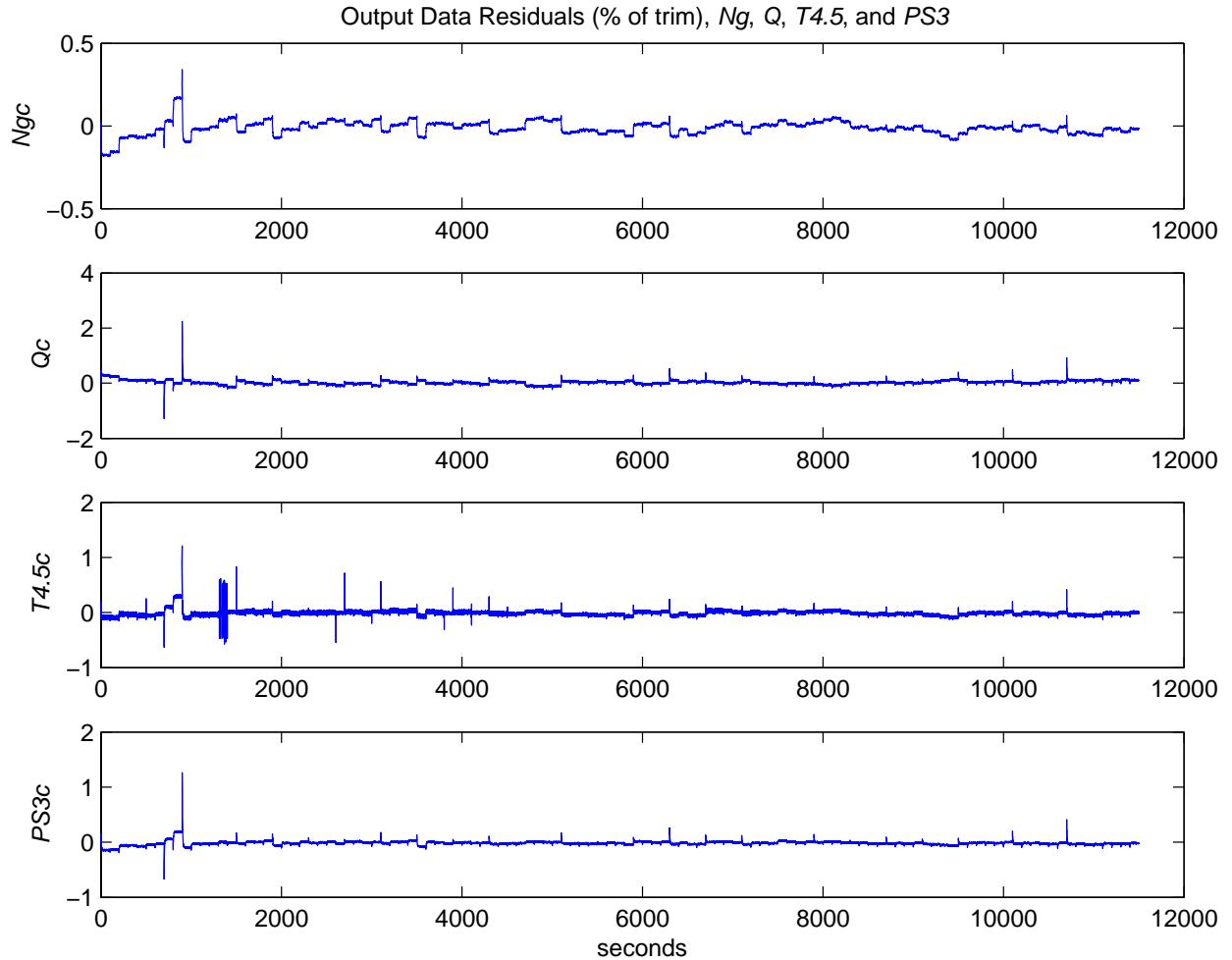


Figure 7.—Residuals of corrected output variables, difference between estimated and actual, % of trim.

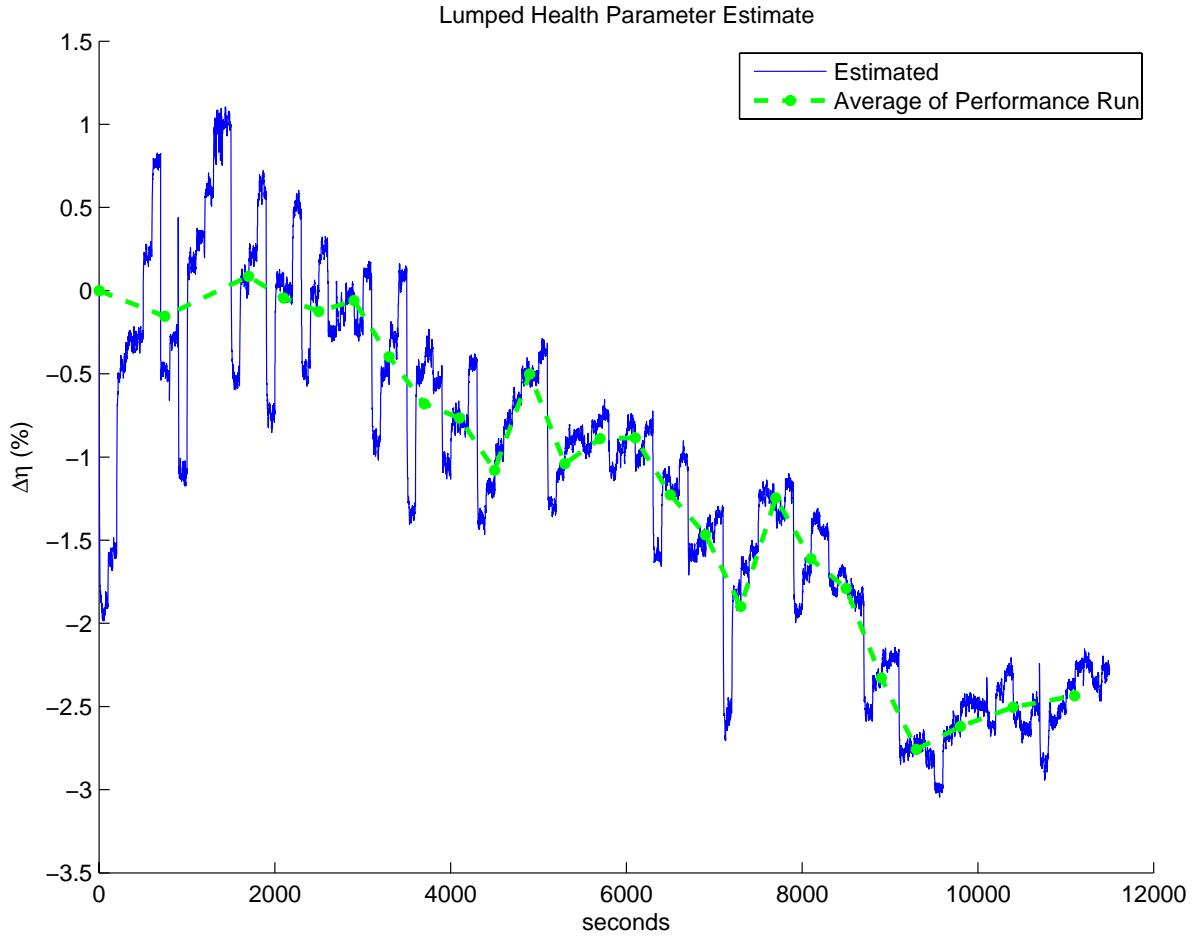


Figure 8.—Efficiency estimate (%) using Kalman filter and average estimate of data gathered in each performance run, deviations from trim.

digital measurement of fuel flow or $PS3$, leaving only $T4.5$, Q and Ng from the previously used set (ref. 22). Since the data seem to support a strongly linear relationship between Wf and Ng and Wf and Q , unaffected by degradation, Ng and Q can be used to estimate a value for Wf . Since $T4.5$ is the only measured variable that is affected by deterioration, a Kalman filter must be developed using a new M matrix. With the reduced data set, it is assumed that the total efficiency shift ($\Delta\eta$) corresponds to the total shift in turbine gas temperature, i.e., the matrix M is computed such that $\Delta T4.5 = M\Delta\eta$ (the amount $T4.5$ is shifted for a given value of Wf is proportional to the shift in efficiency).

A “minimum variance” estimate of fuel flow \hat{Wf} may be generated as the weighted sum of Q and Ng , which have a linear relationship to Wf . Thus

$$\hat{Wf} = \frac{\sigma_Q^2}{\sigma_{Ng}^2 + \sigma_Q^2} \frac{Ng}{\Delta Ng / \Delta Wf} + \frac{\sigma_{Ng}^2}{\sigma_{Ng}^2 + \sigma_Q^2} \frac{Q}{\Delta Q / \Delta Wf} \quad (6)$$

where the delta terms represent the steady state gains of the variables (the slopes of the lines from figures 2 and 3), and σ_x is the standard deviation of the sand ingestion data. Thus the relative weight given to each of the two measurements in equation (6) is related to the spread of the data around the straight line representing the slope; the tighter the relative fit, the greater the weight. (This is an approximation of the minimum variance estimate based on steady state data, in a true minimum variance estimator, the measurement noise variance of each variable would be used.) The Wf residuals (difference of estimated and actual) are shown in figure 9; the large values near the beginning correspond to the two low power points which are out of the linear range. Figure 10 shows the efficiency shift estimated from the “time” sequences generated by stretching out the steady state data; the estimates using both actual Wf and estimated Wf are presented for comparison. Although noisy, the plot has the correct downward trend (except for the two low

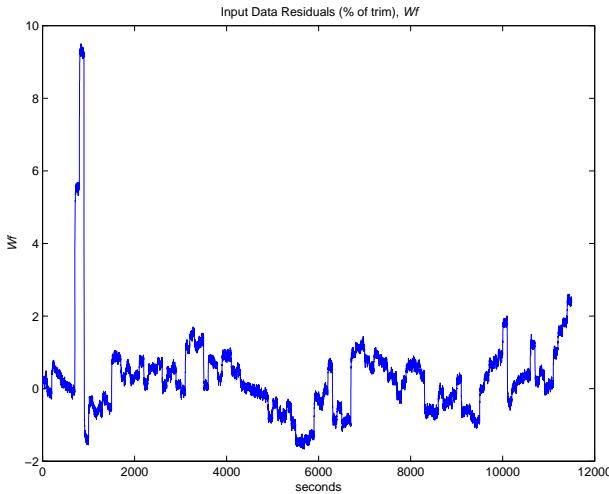


Figure 9.—Residuals of corrected fuel flow, difference between estimated and actual, % of trim.

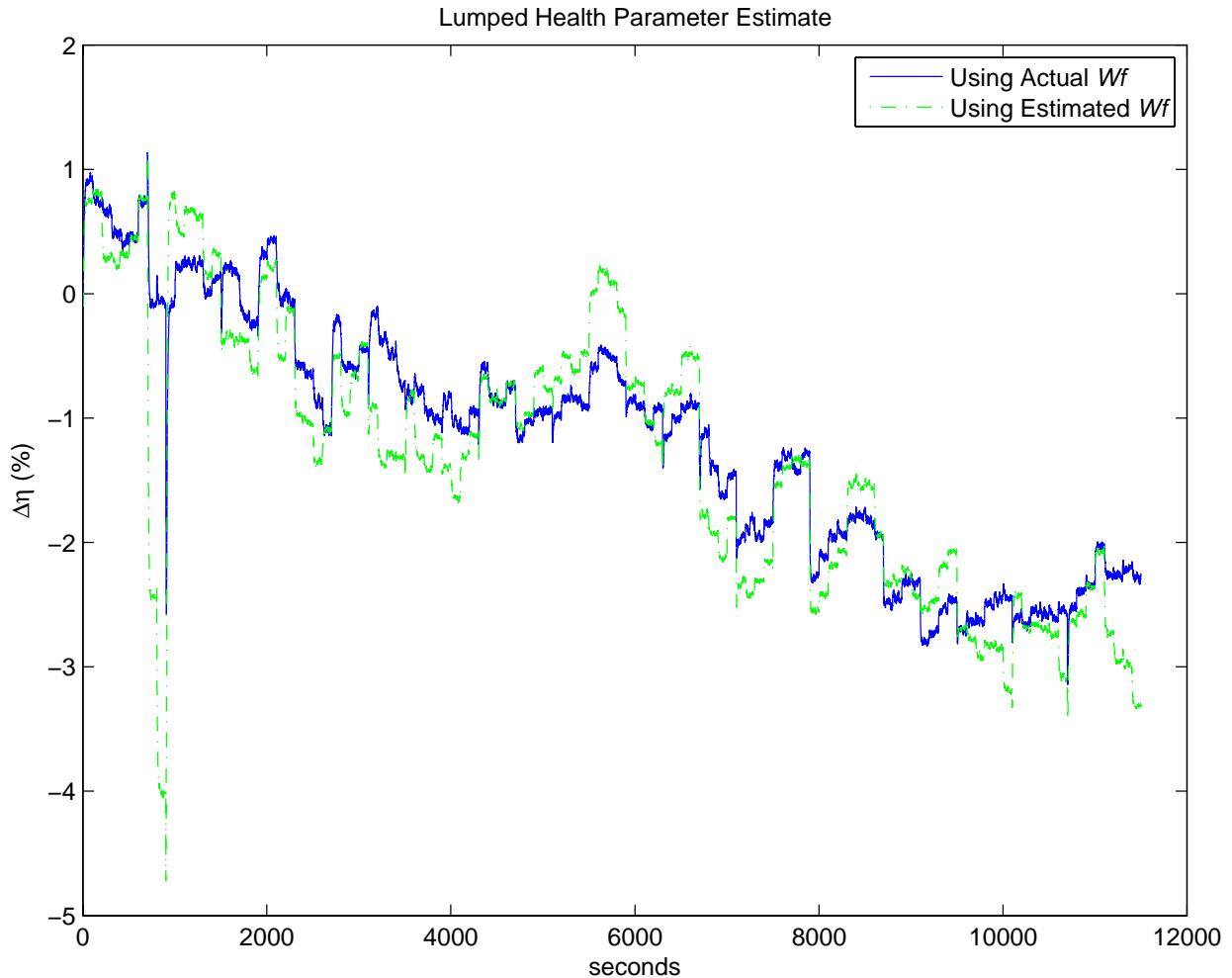


Figure 10.—Shift in efficiency (%) computed using actual and estimated W_f .

power points near the beginning) and approximately correct total efficiency shift. Again, even though the estimated efficiency here is a combined effect, in the field, degradation as a result of sand erosion is primarily limited to the compressor efficiency, so the technique would also be valid under normal circumstances for desert operation.

The on-line compressor health estimation tool has now been demonstrated and validated using a data set similar to what is currently available on most T700 engines. The estimator will next be applied to actual in-flight T700 data. The level of degradation of the engine components is not known, so the results cannot be validated. The purpose is to show that the estimator produces results that could be interpreted, given more information about the engine.

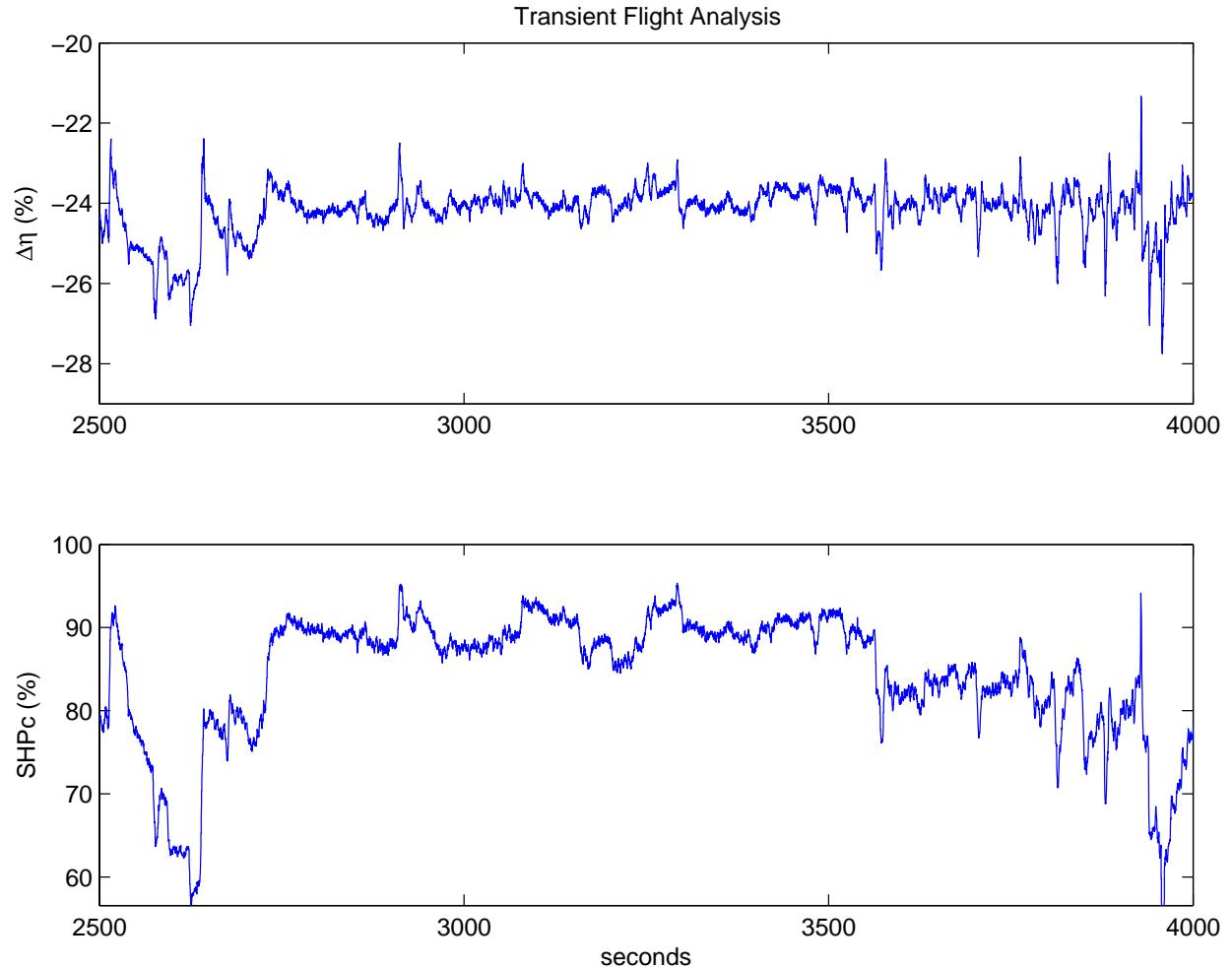


Figure 11.—Efficiency shift estimate (%) and corrected SHP (%) in transient flight from HUMS data.

Evaluation Using HUMS Data

Health Usage and Monitoring System (HUMS) data were obtained from an in-service T700-GE-701C engine, which is a different version of the engine that was used to scale the model. The operating environment for the aircraft with this engine is unknown to the authors. The data available included Ng , Q , $T4.5$, Np , and ambient conditions. Once the data were corrected, Ng and Q were used to estimate the unmeasured Wf . Data from a single flight, takeoff through landing, were used to test the transient capability of the estimator. The flight covered nearly the complete power range of the engine, and the estimator is valid over only about the upper half, based on the sand ingestion data used to determine its model. Figure 11 shows the efficiency estimate as well as the power level over a portion of the flight where the model is valid. The power level varies about 40 percent, yet the compressor efficiency estimate is

fairly stable, varying generally less than 2 percent during transients and well under 1 percent in the steadier power regions. The large magnitude of the estimated efficiency shift (shifted 24 to 25 percent from trim) is probably due to differences between the -401 and -701C engines that would result in different scaling or trim values for the -701C linear model. Note that the estimate is used to detect an efficiency change over time, so the deviation from trim is not relevant and is, in fact, arbitrary. Analysis using the HUMS data showed that the efficiency estimate varies slightly but linearly with power over a wide range of power levels, indicating that a gain adjustment within the estimator would provide a constant estimate across the linear range, or that the apparent component efficiency shift actually varies with power (ref. 23). There is no way to validate the estimate obtained with the HUMS data because there was no independent testing of the component efficiency.

Sources of Error

Many assumptions were made in order to perform the analysis and generate the results described in this paper. Some were simplifications, others were due to lack of information, and still others were the result of the interpretation of the sand ingestion data. The ramifications of these assumptions are discussed in this section.

The estimation of $\Delta\eta$ included the effect of $\Delta\eta_{\text{Comp}}$ and $\Delta\eta_{\text{GG}}$ from the sand ingestion data because the corresponding columns of M were determined to be nearly linearly dependent, since changes in η_{Comp} and η_{GG} have very similar effects (ref. 19). Even though the system was intended for use in the desert where most deterioration occurs in the compressor ($\Delta\eta \approx \Delta\eta_{\text{Comp}}$, $\Delta\eta_{\text{GG}} \approx 0$), this simplification appears valid for the more general case.

In a turboshaft engine, the apparent degradation level can appear different at various power conditions (ref. 20). This was seen to a small extent in the sand ingestion data (the stair-stepping in figure 8 tended to be small and would probably not be noticeable using noisy flight data), and even though it was noted with the HUMS data, where the efficiency estimate varied linearly with power, the Kalman filter could have easily been rescaled to produce a constant efficiency estimate across the power range of interest. This may be related to the assumption that the steady state gain of the engine variables to fuel flow does not change with deterioration; unaccounted-for changes in this relationship would appear as efficiency variations with power.

In the test data, Ng and Q did not noticeably shift with engine degradation. This result was unexpected because it means that SHP (which equals $Q \times Np$) versus Wf does not change with deterioration, although $T4.5$ versus SHP does increase. Since Ng and Q were used to estimate fuel flow in the cases with the limited data set such as might be available to engines without a FADEC, it introduces a potential source of error. If Ng and/or Q were to shift as the engine deteriorated, this approximation would not be valid, even though this contradicts the sand ingestion data.

Power turbine speed was not accounted for as an input to the model (it was present but scaled by a small number) because it seemed to be uncorrelated to the engine outputs. Although it is maintained essentially constant, when corrected the change was significant. Since the correction factors are based on ambient conditions and Np is controlled to an absolute value, Q was considered to be a more significant variable than SHP for modeling purposes. The fact that Np was not used as a model input may have an effect on transient operation.

Much of the literature attributes degradation due to sand ingestion primarily to compressor efficiency, considering degradation of other components insignificant. As long as the assumption is correct in the field, estimation of compressor efficiency alone will produce a meaningful value; otherwise, as in the sand ingestion data where η_{Comp} , η_{GG} , and η_{PT} all changed, the results could be misleading (unless the effect of variations in other health parameters and $\Delta\eta_{\text{Comp}}$ are nearly linearly dependent).

Health parameters besides efficiency, such as flow capacity, are not accounted for at all in the current modeling. Here again, this has the potential to produce misleading results if shifts due to flow capacity are attributed to efficiency and their influence is different.

All of the data used to scale the model are from a test cell. Extra variation in the data due to such factors as altitude and air speed is not seen here. These variations might be harder to eliminate through parameter correction, making the linear relationship more complicated. This might require the model to incorporate variable gains scheduled on altitude and other variables. However, preliminary analysis of the HUMS data did not reveal a dependence on altitude or air speed.

An attempt was made to eliminate from analysis the HUMS data that were affected by such confounding factors as the anti-ice system being on. The model might need to be rescaled to account for these types of factors.

Conclusions

The on-line health assessment tool for the T700 turboshaft engine produced very consistent, repeatable results, even with transient data, and the variation was acceptably small, generally within 1 percent. There is however a need to validate the fuel flow estimate or incorporate an actual fuel flow measurement. Even though the Kalman filter was based on a different engine model, the results were remarkably good, providing justification that this type of algorithm should be investigated further for inclusion in future condition-based maintenance systems. The wide power range covered by the piecewise linear model makes the algorithm extremely attractive for this application because it is so easy to implement. In a sand environment, it provides a relative compressor efficiency value, which can be used to determine fitness for service similar to the way a HIT check does, and it also provides the ability to track performance changes to detect abnormal wear quickly.

Appendix

Data correction to standard day conditions is performed using the following relationships. First, the parameters δ and θ are calculated as

$$\delta = \frac{P}{P_0}, \quad \theta = \frac{T}{T_0}$$

where P_0 and T_0 represent the standard day conditions in full scale ($P_0 = 29.92$ in. Hg (14.696 psi) and $T_0 = 519$ °R) and P and T represent the measured pressure and temperature on the engine. Using these values, the engine variables are corrected as

$$Wf_c = \frac{Wf}{\delta^{\alpha}}$$

$$T_c = \frac{T}{\theta^{\beta}}$$

$$N_c = \frac{N}{\sqrt{\theta}}$$

$$Q_c = \frac{Q}{\delta}$$

where the exponents α and β are derived from theoretical and empirical data for each engine type, but tend to be about 0.5 and 1.0, respectively (ref. 24).

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1. REPORT DATE (DD-MM-YYYY) 25-06-2007			2. REPORT TYPE Technical Memorandum		3. DATES COVERED (From - To)
4. TITLE AND SUBTITLE Toward a Real-Time Measurement-Based System for Estimation of Helicopter Engine Degradation Due to Compressor Erosion			5a. CONTRACT NUMBER		
			5b. GRANT NUMBER		
			5c. PROGRAM ELEMENT NUMBER		
6. AUTHOR(S) Litt, Jonathan, S.; Simon, Donald, L.			5d. PROJECT NUMBER		
			5e. TASK NUMBER		
			5f. WORK UNIT NUMBER WBS 561581.02.07.03.05		
7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES) National Aeronautics and Space Administration John H. Glenn Research Center at Lewis Field Cleveland, Ohio 44135-3191			8. PERFORMING ORGANIZATION REPORT NUMBER E-16059		
9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES) National Aeronautics and Space Administration Washington, DC 20546-0001 and U.S. Army Research Laboratory Adelphi, Maryland 20783-1145			10. SPONSORING/MONITORS ACRONYM(S) NASA, ARL		
			11. SPONSORING/MONITORING REPORT NUMBER NASA/TM-2007-214843; ARL-TR-4087		
12. DISTRIBUTION/AVAILABILITY STATEMENT Unclassified-Unlimited Subject Categories: 07 and 63 Available electronically at http://gltrs.grc.nasa.gov This publication is available from the NASA Center for AeroSpace Information, 301-621-0390					
13. SUPPLEMENTARY NOTES					
14. ABSTRACT This paper presents a preliminary demonstration of an automated health assessment tool, capable of real-time on-board operation using existing engine control hardware. The tool allows operators to discern how rapidly individual turboshaft engines are degrading. As the compressor erodes, performance is lost, and with it the ability to generate power. Thus, such a tool would provide an instant assessment of the engine's fitness to perform a mission, and would help to pinpoint any abnormal wear or performance anomalies before they became serious, thereby decreasing uncertainty and enabling improved maintenance scheduling. The research described in the paper utilized test stand data from a T700-GE-401 turboshaft engine that underwent sand-ingestion testing to scale a model-based compressor efficiency degradation estimation algorithm. This algorithm was then applied to real-time Health Usage and Monitoring System (HUMS) data from a T700-GE-701C to track compressor efficiency on-line. The approach uses an optimal estimator called a Kalman filter. The filter is designed to estimate the compressor efficiency using only data from the engine's sensors as input.					
15. SUBJECT TERMS Turboshafts; Maintenance; Degradation; Kalman filters; Ingestion (Engines); Compressor efficiency					
16. SECURITY CLASSIFICATION OF:		17. LIMITATION OF ABSTRACT	18. NUMBER OF PAGES 20	19a. NAME OF RESPONSIBLE PERSON Jonathan S. Litt	
a. REPORT U	b. ABSTRACT U			c. THIS PAGE U	

